RICE LEAF DISEASE IDENTIFICATION USING DEEP LEARNING

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled Rice Leaf Disease Identification Using Deep Learning", submitted by ID: 201-14-3188 **Saquline Suja Saque** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **15-07-2024.**

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Dr. Md. Zahid Hasan, Associate Professor, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

We have developed an online app to identify rice leaf diseases automatically through deep learning models. The gravest challenges to crop production and food safety are posed by rice leaf diseases like Tungro, Blast, Bacterial Blight, and Brown Spot. Several models were used in this study such as MobileNetV2 individually, ResNet50V2 separately, and DenseNet201 on its own as well as a combination model which is made up of ResNet50V2 and DenseNet201 known as the hybrid model. Following the validation process the hybrid model achieved an accuracy rate of up to 99.83% with 99.77% during training while MobileNetV2 got 98.80% in the validation stage after being trained at 98.30%. ResNet50V2 reached 98.30% on validation after hitting 99.00% during training while DenseNet201 had 98.00% after 96.30% for training. The user-oriented design lets people upload images and choose a classification model. This gives quick and correct results for real-time use. The approach makes it easier to identify diseases and helps agricultural professionals and farmers access them easily so that they can be managed promptly and effectively. To solve this problem, we have brought these models onto a platform where they are easy to reach. This is expected to reduce the effects of leaf diseases on rice significantly hence promoting sustainable farming as well as food security.

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ML	Machine Learning
DL	Deep Learning
CNN	Convolutional Neural Network

CHAPTER 1

Introduction

1.1 Overview:

Rice is an important crop for ensuring food security for millions of people across the globe. However, leaf diseases pose a threat to its productivity. These diseases are difficult to diagnose because they share common symptoms. In addition, the pests are often mistaken for diseases. Visual inspection which is the traditional method of detecting these diseases is usually time-consuming and unreliable. This leads to delayed diagnosis and inappropriate control measures. Therefore, there is a need for faster and more accurate identification methods that can help in reducing losses caused by these diseases as well as ensuring continued food production. One of the most recent technologies that have been developed is deep learning which falls under artificial intelligence.

The most significant crop for providing food security for millions of people worldwide is rice in agriculture. A lot of diseases, including leaf ones, can attack rice plants. However, detecting these diseases using traditional methods has some challenges. First and foremost, they are time-consuming since they rely on visual observation. Secondly, they are subjective meaning that delays in diagnosis and wrong control measures can be made. The only way to reduce crop losses due to diseases and ensure increased food production lies in having more accurate and faster identification methods. In the past few years, deep learning which is a subset of AI has been used in automatic image recognition and classification tasks and it seems quite promising.

To propel the capacity of identification of rice leaf diseases using digital images in the field, the study focuses on the efficiency of deep learning models. The systems are trained using datasets made of pictures of healthy and unhealthy leaves of this cereal plant to further technological advancement in agriculture and improve how diseases are managed during rice cultivation which is more efficient than current methods. This research investigates new approaches towards solving complex challenges experienced in paddy farming through deep learning techniques thus creating sustainable food production systems.

1.2 Background and Present State

The research on utilizing deep learning for identifying diseases in rice leaves has a strong foundation in the literature, which emphasizes the pivotal role of rice in ensuring food security globally, especially across Asia, Africa, and Latin America. Diseases in rice leaves such as blast and bacterial blight have been notorious for substantially reducing both the quality and quantity of agricultural produce thereby posing big challenges. To facilitate a clear understanding of the key concepts and methodologies employed in this research on "Rice leaf diseases Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Hybrid model," it is imperative to establish a foundation through preliminaries and the clarification of terminologies. Deep Convolutional Neural Networks (CNNs), a cornerstone of image analysis, are employed to harness intricate patterns in medical imaging. Detection refers to the identification of Rice leaf disease images. Throughout this research, these terminologies are utilized cohesively to explore the deep CNNs and hybrid models in the comparative analysis of detection and segmentation approaches. Establishing a common understanding of these preliminaries is essential for readers to delve into the intricacies of the study and comprehend the nuances of advanced techniques employed in pneumonia diagnostics. For instance, some studies using image data have demonstrated how well these methods can recognize patterns compared to when a human being is the one doing it. Therefore, speed as well as accuracy in disease diagnosis are likely to be greatly improved among the farmers who rely most on this traditional approach. Nevertheless, despite these facts widely acknowledged gap exists.

1.3 Problem Statement

One of the ways farmers diagnose rice leaf diseases – involves traditional methods, which are time-consuming, labor-intensive, and obtain some incorrect results, thus resulting in delays of the preventive measures and enormous crop losses. The availability and timely identification of diseases are the prerequisites for the implementation of the right measures and hence food safety. The traditional methods of diagnosing the disease depend solely on the diagnoses of the expert. This can be subjected and can also be prone to errors. Given the current state of rice farming, which has expanded significantly, and the discovery of new disease variants, the time to come up with a machine-based system that is precise, speedy, and efficient is now. The main aim is to build a deep learning algorithm-based model to detect and classify rice leaf diseases in real-time, a technological intervention that will reduce disease foci and the number of crops lost.

1.4 Objectives

This thesis stems from the urgent need to address the challenges posed by rice leaf diseases and enhance the sustainability and productivity of rice cultivation worldwide. Leaf diseases not only threaten food security by reducing crop yields but also impose economic burdens on farmers and disrupt food supply chains. Traditional methods of disease identification are inadequate in scale, accuracy, and efficiency, highlighting the necessity for innovative solutions. The rapid advancements in deep learning and computer vision present an exciting opportunity to revolutionize rice leaf disease identification. By harnessing these technologies, we can develop automated systems capable of rapidly and accurately diagnosing diseases, empowering farmers with timely information to implement effective disease management strategies. The potential impact of such systems extends beyond agriculture, touching upon broader goals of global food security and sustainable development.

1.5 Scope and Limitations

This study addresses various dimensions of rice growing problems, considering that it is a staple food worldwide. Rice plants are very sensitive to different leaf diseases including blast, sheath blight, brown spot, and bacterial blight. These diseases can lead to high losses in yields and affect the quality of harvest in a way that may threaten millions of farmers' lives as well as feed billions of people. Their identification through traditional means which require expertise for visual inspection is slow, tedious, and likely inaccurate most times. Factors like climate change enhance the spread of rice leaf diseases besides. Disease patterns are changed and crops become more vulnerable to this effect then. Additionally, the expansion of farming areas brings new challenges for disease control since it introduces them too. Furthermore, many smallholder farmers who make up most of the producers of rice lack proper diagnostic tools as well as resources for managing these illnesses effectively. It's clear from these that finding ways to identify – and subsequently treat – such infections are vital if we want to ensure food security today. The current research is aimed at creating systems capable of recognizing automatically different types of leaf diseases found on rice plants using techniques based on deep learning and transfer learning. These systems will improve disease detection accuracy and speed, which can in turn losses caused by illnesses and ensure a consistent food supply. However, it is important to note that dealing with this issue at its full scale will require more than technological advancements; Equitable availability of modern diagnostic equipment, promotion of sustainable farming encouragement of community resilience are all necessary for effectively addressing challenges related to rice leaf diseases.

1.6 Report Organization

Chapter 1: Introduction In this chapter we have overviewed our technology and talked about various problems, what was the objective of our project, and also with scope and some limitations of our project.

Chapter 2: Here we discuss the related works that we have done in our project and also the comparison between those existing works and what are the open issues.

Chapter 3: Research Methodology The research methodology chapter outlines the approach taken to conduct the study. what kind of model and how we use those in our project talks in this chapter.

Chapter 4: Here we discuss how we implemented our project, various system testing, and what pain models we used.

Chapter 5: Result and analysis This chapter presents the experimental results of our project on how we did and what we obtained from the application of transfer learning and deep CNNs and the Hybrid model in rice leaf disease detection. and made a web application to ensure the validation of our study.

Chapter 6: Impact on Society We talked here about how our technology is making an impact in our daily lives and how the society of the course is created and we also talked about the ethical expectations here and then we tried to highlight something about the sustainable plan.

Chapter 7: Summary, Conclusion, Recommendation, and Implications we discussed the conclusion of our project and how to work on it in the future and create a better outcome.

1.7 Summary

Rice is one of the most important crops in the world and is constantly being threatened by leaf diseases, which are nearly impossible to detect using old visual diagnostics. These methods are slow and not completely reliable. The demand for quicker and more reliable diagnostic systems is the need of an hour. Deep learning has evolved in recent years and has proven itself to be an amazing tool for various tasks such as object classification. In this example, Deep Convolutional Neural Networks (CNNs) show promise for disease detection in rice cultivation. The study will propose a four-stage plan for this problem such as data collection, network architecture, and data preprocessing using artificial neural network) in image processing. The project's main purpose of research consists of the development of a real-time deep learning algorithm to recognize and classify rice leaf diseases, thereby reducing crop losses and producing more food. This scientific endeavor aims to automate the disease management systems and make them specific along with the timely ones, thus, joining in with the general principles of local food security and sustainable agriculture. The availability of new diagnostics and modern agricultural practices is also key to this.

CHAPTER 2
Literature Review

2.1 Overview

The existing methods for the identification and classification of rice leaf diseases through observation by specialists have been, for a very long time, a time-consuming and inaccurate process. Most recent studies involved deep learning approaches to the possibility of automatic works, which have significantly increased the accuracy and efficiency. The usefulness of convolutional neural networks (CNNs) in the classification of different rice leaf diseases with high precision was proven. Ahmed et al. 2019 also demonstrate that transfer learning and hybrid models have shown very good results in terms of model performance improvement. Pallathadka et al. (2022) highlighted the requirement for technology such as that because of the multitude of diseases such as blast, bacterial blight, brown spot, tungro disease, and other traditional methods are facing the difficulty of managing them effectively. As a further result, the implementation of transfer learning in addition to hybrid models has also yielded excellent results in the improvement of model performance. Shreya & Kamal (2020) discussed the development of mobile applications utilizing CNNs for real-time disease diagnosis, highlighting the practical benefits for farmers. This project builds on these foundations, employing hybrid models such as ResNet50V2, DenseNet201, and MobileNetV2 to achieve superior classification accuracy and robustness, aiming to provide a scalable and user-friendly solution for rice disease management in the agricultural sector.

2.2 Related Works

Akter et al., (2019) employed Deep Learning methods to identify plant diseases, aiding farmers in timely detection for prompt action. They utilized 2589 original images for testing and 30880 images for training, implementing the Caffe framework. Their model achieved a 96.77% prediction accuracy through 10-fold cross-validation.

Pre-trained and suggested deep learning models were compared by E. ERDEM et al. (2021). Deep learning structure accuracy is 88.62%. The new deep neural network Approximated VGG16 (88.78%) and VGG19 (88.30%) accuracy scores. The model has a higher recall value (97.43%) and F1-Score (91.45%) than VGG16 (91.22%) and VGG19 (91.19%).

T. Frondelius et al. (2022) give methods: Representative multidisciplinary databases were examined for diagnostic and prognostic prediction models. To find publications without predictive research in their titles or abstracts, a long list of validated search phrases was included.

Another approach Bilal Khan et al., (2023), focused solely on RGB value extraction from affected rice leaf areas via image processing. A Naive Bayes classifier categorized diseases into Bacterial leaf blight, Rice blast, and Brown spot with an accuracy exceeding 89%.

The detrimental effects of bacterial infections and insects on rice plants are widely recognized, and this is a significant concern for areas where rice is a staple grain. (Kaur et al., (2021) This paper suggests a transfer learning model with great accuracy that can offer a mobile solution. They use transfer learning architectures to achieve an average cross-validation accuracy of 98.79%.

Vasantha et al., (2021) Rice, also known as Oryza Sativa, is a cereal grain that is a staple food for about half of the world's population, primarily in Asia and Africa. this paper uses various ML for classification. Deep feature-based SVM accuracy is 97% and Deep CNN accuracy is 95%.

Maniyath et al. (2018) utilized random forest with a Histogram of Oriented Gradient (HOG) for feature extraction, achieving a 92.33% accuracy in classifying healthy and diseased leaves.

Moreover, Kaur et al., (2021) employed image processing and machine learning for rice plant disease detection and classification. They applied K-means clustering for segmentation and SVM for classification, obtaining 93.33% and 73.33% accuracy on training and test datasets, respectively. However, the authors claimed higher accuracies in both datasets through their methodology.

Machine learning-based pneumonia risk score models that had previously been published were defeated by this tactic given by Y. Ge et al. (2019). To avoid pneumonia following stroke at a cheap cost. The attention-augmented GRU exhibited the highest specificity for pneumonia within 7 days, with a PPV of 0.32 and NPV of 0.99.

Pugoy & Mariano, (2011) To develop effective nutrition and disease management techniques, rice-related institutions like the International Rice Research Institute rely on manual eyeball exercises to evaluate a rice plant's health through its leaves. They used the K-means clustering algorithm to group related regions into clusters. And determine the suspected diseases of the rice leaf.

2.3 Comparison between existing works

Having a focus on their performance, ethical effects, and research potential, the study studied the use of deep learning and transfer learning methods for automated rice leaf disease identification. First, the research showed that deep learning models can reliably identify a range of rice leaf diseases, including bacterial blight, blast, sheath blight, and brown spot. Deep learning algorithms have demonstrated encouraging outcomes in enhancing disease diagnosis and management through the utilization of extensive datasets of superior-quality images. This has led to an increase in agricultural productivity and increased food security.

The study added the ethical problems related to automated disease detection, such as those involving data privacy, bias, accessibility, transparency, and economic effects. The study addressed the importance of responsible technology deployment and stakeholder engagement to encourage equitable and environmentally friendly agricultural growth by tackling these ethical challenges. The study also identified several directions for future investigation, such as the creation of deeper learning models with greater resilience, the improvement of automated disease identification tools' accessibility and scalability, the incorporation of new data sources to enhance their predictive power, and interdisciplinary partnerships to evaluate the wider effects of technology adoption in agriculture. In conclusion, the comparative research demonstrated how automated methods for deep 14 learning and transfer learning might be used to identify rice leaf diseases, thereby addressing important issues related to agricultural productivity, food security, and sustainability. Through the advancement of technological innovation, ethical considerations, and interdisciplinary collaboration, this study makes a valuable contribution to the ongoing efforts aimed at utilizing technology for the betterment of agricultural communities across the globe.

TABLE 2.1: Comparative Analysis Table

Study	Image type	CNN Model	Accuracy
Akter et al., (2019)	Plant diseases	Convolutional Neural Network (CNN)	Accuracy 96.77%
Rahman et al. (2020)	digital x-ray images	Deep convolutional Neural Network (CNN)	The classification accuracy of normal and pneumonia images, bacterial and viral pneumonia images, and normal, bacterial, and viral pneumonia were 98%, 95%, and 93.3%, respectively
GM.H. Gourisaria et al. (2021)	Chest X-rays	Convolutional Neural Network (CNN)	Sensitivity = 90.07% and Specificity = 92.16%
Erdem, E., & AYDİN, T. (2021)	lung images	Convolutional Neural Network (CNN)	accuracy results of VGG16 (88.78%) and VGG19 (88.30%), which are among the popular deep-learning architectures can be approximated
Sharma et al. (2020, January)	chest X-ray	Deep convolutional Neural Network (CNN)	train the proposed CNNs using both the original as well an augmented dataset and the results are reported
Labhane et al. (2020)	chest x-ray images	Convolutional Neural Network (CNN)	The results were then tested using 854 pneumonia and 849 normal images and an accuracy of over 97% was obtained from all models
Yao et al. (2021)	chest X-ray (CXR) images	Convolutional Neural Network (CNN)	The algorithm obtained a 39.23% Mean Average Precision (mAP) on the X-ray image

2.4 Open Issues

Although receiving optimistic data, there are myriad obstacles still unsolved. Data quality is the most important issue to be addressed, with the robustness of the model's good programmed via involving the largest variety of disease stages and environmental conditions. Implementing real-time detection in the field is complicated and may vary through the quality of the image and field conditions. The mystery of the deep learning models is such that they worry often about the lack of explanation, which is why the focus should be on the patient experience in the diagnostic process. The issue of scaling across multiple geo-locations should also be handled, in addition to designing a friendly application interface that will engage farmers. Every day product updates for both the new disease strains and the changing conditions are a need. Integrating the tool in the already existing farming practices and treating the moral issue of data privacy and equal availability are the main points for the project's success.

2.5 Summary

It is straining and oftentimes wrong to use the conventional diagnostic techniques for the identification of leaf diseases coming upon the improvement in the deep learning sector, particularly in CNNs which have realized higher accuracy and efficiency of the analysis. The use of hybrid models and transfer learning went a step further in accuracy hence their detailed applications in mobile apps for real-time diagnostics. They have various deep learning and machine learning techniques which have been gaining high accuracy in disease detection in agricultural studies. Despite these eye-catching findings, problems remain to be addressed, such as ensuring data quality, achieving real-time field detection, improving model interpretability, and scaling solutions across regions. Therefore, the design of a user-friendly interface, delivery of regular updates, and integration of existing practices are key in the development of ethical data storage and sharing practices. In summary, deep learning methods hold significant promise for improving rice leaf disease management and supporting farmers with scalable, efficient solutions.

CHAPTER 3
Methodology/ Requirement Analysis & Design Specification

3.1 Overview

Deep learning models like ResNet50V2, DenseNet201, MobileNetV2, InceptionV3, and EfficientNet can be used in this research. It will involve creating a dataset that has pictures showing healthy and infected leaves and then applying these models. An instrument research topic comprises several steps which include: collecting different types of Tungro, Blast Bacterial blight Brown spot alongside normal ones, preprocessing them such as making sure all images are of equal size by adjusting their dimensions so they become 256 x256 pixels, normalizing pixel values so that they range from 0 to 1 and data augmentation for diversity during training. After that, the clean data set will be utilized to teach deep learning models what features are associated with various rice leaf diseases. The trained models will then be validated on different data sets or tested to see how well they can classify rice leaf diseases with regard to their performance accuracy levels. This will involve comparing their accuracy along with other things such as computational speed so as not just one but many models should do this work also checking if they can work well even if used for other crops as well. The findings should then be evaluated to identify where the models are strong or weak and what could be done to make Automated Rice Leaf Disease Identification better. In conclusion, we discuss what impact these results have on agriculture, and food security and propose areas where future research could focus on improving Deep Learning Models efficiency within Agricultural Systems. Through this research, the aim is to advance agricultural technology and contribute to the development of innovative solutions for disease management in rice cultivation.

3.2 Proposed Methodology

Convolutional Neural Networks (CNNs) where one of the families of deep learning networks, have in recent years been employed with great success for detailed analysis of images. This development has been invoked largely by the fact that CNNs can automatically learn to build increasingly complex representations of images while adding just a small amount of preprocessing. The essential building blocks of CNNs are comprised of convolutional, pooling, and relu layers, fully connected layers, and several activation functions. Schematically, a CNN is a multi-layer structure that chips away at information, thus allowing higher-level features to be identified in the input image. They will then be focal points of the performance of such tasks as classification, object detection, and segmentation.

ResNet50v2: This text towards ResNet50V2 mainly aims at the ResNet (Residual Network) band of RS Network, which was the first of its kind to use residual connections in the deep neural network model. ResNet50V2 is the same as ResNet50 but it has a few enhancements introduced and inherited some characteristics that are got from having residual modules in its architecture. It has become popular in the computer vision community due to its strong performance and ease of use for tasks. The ResNet50v2 design has 50 layers, and it makes use of skip connections to prevent the network from facing the problem while it is learning deeper representations (Sarada et al., 2023).

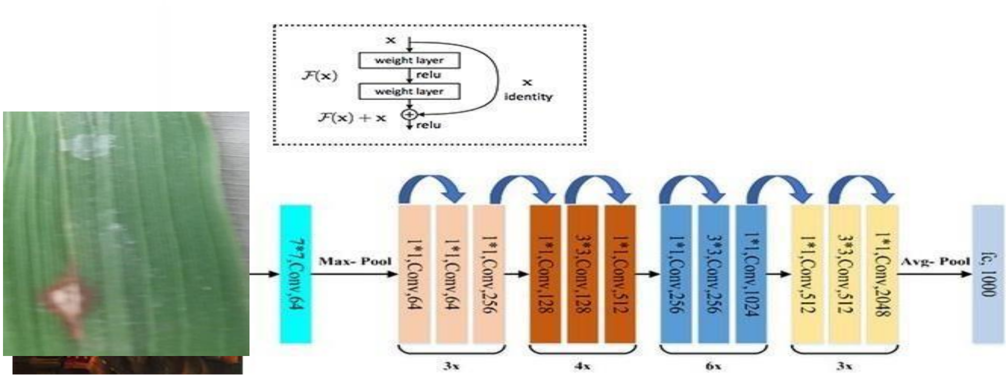

Figure 3.1: Schematic representation of ResNet50v2

DenseNet201: DenseNet201 is designed to enhance the depth and training efficiency of deep learning networks by utilizing shorter connections between layers. Unlike conventional architectures, DenseNet201 establishes dense connections between every layer and all preceding layers. For instance, the first layer is connected to subsequent layers, and this connectivity pattern continues throughout the network.

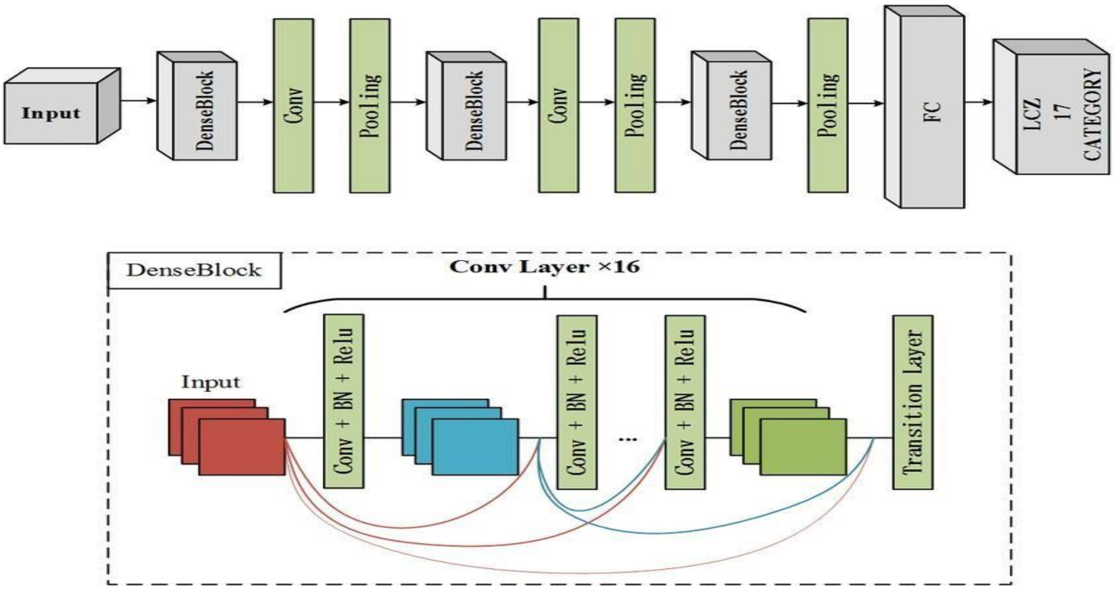

Figure 3.2: DenseNet201 (Bilal Khan et al., 2023)

MobileNetV2: Represents a convolutional neural network (CNN) architecture specifically engineered for optimal performance on mobile devices. This design is centered on an inverted residual structure, wherein residual connections are strategically placed between bottleneck layers. The architecture incorporates lightweight depth-wise (Dwise) convolutions in the intermediate expansion layer to filter features and introduce non-linearity. The initial layer consists of 32 filters, followed by 19 residual bottleneck layers. Figure 4 illustrates the network architecture of MobileNetV2, providing a visual representation for examination.

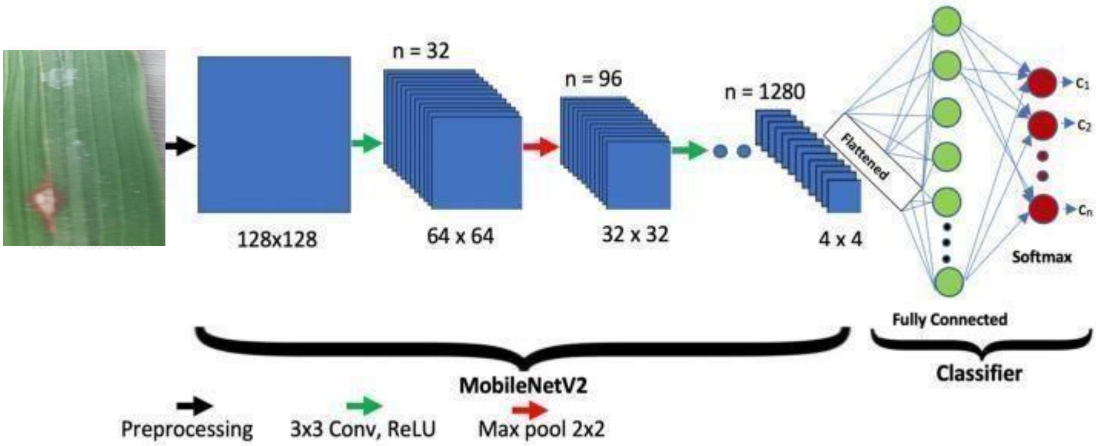

Figure 3.3: Schematic representation of MobileNetV2

Hybrid Model: This hybrid model merges ResNet50V2 and DenseNet201, two pre-trained convolutional neural networks (CNNs), for robust image classification. With input images sized (128, 128, 3), ResNet50V2 and DenseNet201 extract features, keeping their weights frozen. Concatenating the global average pooled outputs facilitates diverse feature representation. A dense layer with 512 ReLU units processes the concatenated features, followed by a dropout layer to prevent overfitting. The output layer, with softmax activation, yields class probabilities for multi-class classification. Compiled with Adam optimizer, categorical cross-entropy loss, and accuracy metric, this model efficiently trains and evaluates, making it suitable for various image classification task

Data Collection Procedure

We collect our data set mainly from Keggle where this data is basically divided into four classes that name is Bacterial Blight, Blast, Brownspot, and Tungro. Total Image is almost 6210. In Bacterialblight we have around 1321 images, in Blast we have 1446 images, also Brownspot we have 1584 images and the last one in Tungro we have almost 1600.

Bacterial blight

Bacterial blight, caused by Xanthomonas oryzae pv. oryzae, is a destructive disease affecting rice plants. Characterized by water-soaked lesions, it leads to leaf wilting, yellowing, and eventually death. Bacterial blight impacts rice yields worldwide, posing a significant threat to global food security and necessitating effective disease management strategies.

Figure 3.4: The image of Bacterial Blight diseases

Blast

Blast, caused by the fungus Magnaporthe oryzae, is a devastating disease affecting rice crops globally. It manifests as small, water-soaked lesions on leaves, stems, and panicles, leading to significant yield losses.


Figure 3.5: The image of Blast diseases

Brownspot

Brown spot, caused by the fungus Cochliobolus miyabeanus, is a common foliar disease of rice plants. It appears as small, oval-shaped lesions with brown centers and yellow halos on the leaves. Brown spot can lead to reduced photosynthetic activity, stunted growth, and yield losses in rice crops, making it a significant concern for farmers worldwide. Effective disease management strategies are essential to minimize its impact on rice production and ensure food security. Brown spot, also known as Helminthosporium leaf spot, is a fungal disease affecting rice plants. surrounded by a yellow halo. Severe infections can lead to extensive leaf damage, reduced photosynthesis, and ultimately yield losses.


Figure 3.6: The image of Brown spot diseases

Tungro

Tungro is a viral disease affecting rice plants and is caused by a combination of two viruses: Rice tango bacilliform virus (RTBV) and Rice tungro spherical virus (RTSV), which are transmitted by the green leafhopper insect. This disease is prevalent in many rice-growing regions of Asia. Symptoms include stunted growth, yellowing of leaves, and reduced grain quality and yield. Tungro poses a significant threat to rice production, requiring integrated pest management practices to control the spread of the disease and minimize its impact on crop yields and food security.

Figure 3.7: The image of Tungro spot disease

3.3 Hardware

Using the verious library, the experiments for this study were carried out on Google CoLab. For dealing with machine learning techniques on Python, TensorFlow, one of the best deep learning libraries, was employed. Each model was created by Google and made accessible through the Google Collaboratory framework after being trained in the cloud using a Tesla graphics processing unit (GPU). For research purposes, the Collaboratory framework offers up to 16GB of random-access memory (RAM) and roughly 360GB of 17 GPU in the cloud. In this study, the pneumonia detection architectures used where the models are original ResNet50v2, MobileNetv2, DensNet201 and Hybrid Model. One architecture was chosen from each category. There is overlap, though, as ResNet is classified as belonging to the depth, width, and multi-path categories. The research leverages programming languages and frameworks such as Python and TensorFlow for the implementation of the deep learning models and associated algorithms. Computational infrastructure, including GPUs for accelerated processing, plays a crucial role in handling the complexity of deep learning tasks efficiently.

3.4 Project Management and Financial Analysis

This section outlines the plan for managing my research project, including timelines, resources, and financial considerations.

Timeline: Develop a detailed timeline outlining the key project milestones and dead-lines for each stage of the research process, including.

- Data collection and pre-processing
- Model development and training
- Evaluation and testing
- Mobile application development
- Documentation and reporting

Roles and Responsibilities: I working in a research group, clearly define the roles and responsibilities of each team member, ensuring everyone understands their tasks and contributions.

Communication Plan: Establish a communication plan outlining how team members will communicate with each other, including preferred communication channels and meeting schedules.

Risk Management: Identify potential risks that could impact the project data availability, technical challenges, and unexpected delays and develop strategies to mitigate them.

TABLE 3.1: Comparative Analysis Table

SN	Components	Estimated Cost (BDT)
01	Hardware/Infrastructure	0
02	Visiting Stakeholders	0
03	Software and Tools	1000

04	Data Collection and Processing	500
05	Documentation and Report Writing	500-1000
06	Miscellaneous (e.g., licenses, tools)	0
07	Contingency (10% of total)	200-300
	Total Estimated Cost	**2500-3000**

3.5 Summary

The focus of this research is to create a computerized system for recognizing rice leaves' diseases by the use of deep learning models such as ResNet50V2, DenseNet201, MobileNetV2, InceptionV3, and EfficientNet. A dataset from Kaggle will be provided that consists of images of Bacterial Blight, Blast, Brown Spot, and Tungro, which will be preprocessed and augmented. The technical architectures of the model will display various characteristics including a hybrid model that merges ResNet50V2 and DenseNet201 for classifying without any gray area which gives more courage to you. Experiments will include the processes of data augmentation, model integration, and training with parameters such as 10 epochs, a batch size of 32, and a learning rate of 0.001. When the study is conducted on Google CoLab using TensorFlow, they will have a detailed project management plan, defined roles, and a communication plan, and will be prepared with strategies for risk mitigation.

CHAPTER 4

Implementation

4.1 Overview

The process of implementation for our rice leaf disease identification project is a phased process that contains several essential tasks. At the very beginning, a dataset that consists of many high-quality images that represent different stages of rice leaf diseases will be collected. Then the pictures will be preprocessed, more specifically by resizing, normalizing, and augmenting to enhance model robustness. Next, three different models will be conducted: such as a mixture of ResNet50V2 and DenseNet201, MobileNetV2, and ResNet50V2, each trained on the preprocessed dataset. On top of that, the models that are trained on transfer learning will use pre-trained weights. The models will be assessed on the basis of metrics like accuracy and loss on both training and validation datasets, which in turn will allow for a comparative analysis to determine the most effective model. When it comes to model optimization and tuning, you need to work with hyperparameters which can be fine-tuned and include methods such as learning rate reduction and dropout to prevent overfitting. The best model will be brought to life in the form of a user-friendly web application which is basically used by farmers to take pictures of rice leaves and get the required information immediately. The system will be extensively tested and validated under different conditions to ensure its proper functioning. Furthermore, the application's performance will be meaningfully tested with real-world data and feedback from agricultural experts. In addition to maintenance and update will involve regularly updating the models with new data to maintain accuracy and effectiveness, as well as continuously monitoring and improving the application based on user feedback and advancements in deep learning technology. This objective system pursues to create a reliable, proficient, and available tool for finding rice plant leaf infections, actually real helping to increase plants' long life and productivity. In addition to maintenance and update will involve regularly updating the models with new data to maintain accuracy and effectiveness, as well as continuously monitoring and improving the application based on user feedback and advancements in deep learning technology. This objective system pursues to create a reliable, proficient, and available tool for finding rice plant leaf infections, actually helping to increase plants' long life and productivity.

4.2 Train Model

The ResNet50V2 and DenseNet201 Hybrid model utilizes two different architectures to enable strong disease classification through image recognition; this is done by taking advantage of the unique feature representations that come with each one. DenseNet201 uses dense connectivity so that all layers can access the feature maps from previous ones. On the other hand, MobileNetV2 employs lightweight depthwise separable convolutions, making it suitable for environments with limited resources such as field cameras for identifying rice leaf diseases. This is a rundown of how the experiment was designed to go:

Data Collection and Preparation:

To create a comprehensive rice leaf dataset, collect images of healthy leaves as well as different diseases such as Blast, Tungro, Bacterial blight, and Brown spot. Standardize the image resolutions by resizing them, normalizing pixel values, and increasing the dataset through augmentation techniques so that the model can be more adaptable.

Image Augmentation:

Image enhancement is used in this stage. Picture augmentation adds fresh data to an existing dataset while preserving its label data. A bigger data set improves model generalization, creation it more lenient to unknown inputs. Data augmentation helped us reach training data objectives. Nevertheless, brightness, contrast, saturation, scaling, cropping, flipping, and revolution were utilized to improve color and position. Data augmentation included random spins from -15 to 15 degrees, inadvertent 90-degree rotations, distortion, bending, vertical and horizontal reversals, skate, and luminous intensity conversion. Each original picture was improved 10 times. A subset of transformations improves a heterogeneous picture.

Model Architecture Selection:

Choose suitable pre-trained models for the hybrid architecture, such as ResNet50V2 and DenseNet201. These models offer different architectural designs and performance characteristics, contributing to the overall hybrid model's effectiveness.

Model Integration:

Integrate the selected pre-trained models into a hybrid architecture. This typically involves concatenating the outputs of intermediate layers from each model and adding custom fully connected layers for classification.

Training:

When a system is being trained, its parameters are adjusted repeatedly to reduce a specific loss function. The number of epochs, which is the number of times the entire dataset is processed, affects how well the model can converge and generalize. It is normal to begin with a moderate number of epochs such as 10 and then decide on the best value by checking the performance of validation. Batch size tells us how many samples are processed before the parameters get updated and this also affects training dynamics and computational efficiency. We try 32-batch size. If we have smaller batches then there will be more frequent updates of parameters but they might take longer time for training while larger ones may speed up the training process. However convergence could be slow. Hence it is important to choose them wisely depending on dataset size and complexity of the model. The step size during parameter updates is decided by the learning rate and is an important factor in optimization stability. To begin with, a moderate learning rate such as 0.001 should be used and modified according to validation performance so that training can be efficient. Adam, RMSprop, and SGD with momentum are among the common optimizers with unique properties impacting convergence speed and stability.
In order to evaluate model performance & tune hyperparameters it’s necessary to split part of the training dataset for validation (validation split). Typically, a portion of the training data 20% is set aside as the validation set. To ensure thorough evaluation strength should be balanced between sizes for both validation sets and training sets while tuning hyperparameters too much can lead to them becoming less effective or overfitting entirely however not enough might cause underfitting altogether but taking everything into account, thoughtful consideration along with iterating over these things will eventually result not only into better-optimized models but also improved performances.

Proposed Methodology

CNN base methods are evaluated using many machine learning classification model performance metrics. AC, precision, recall, F1-score, and confusion matrix are evaluated (CM). TP, TN, FP, and FN are also variables in those measurements (FN).

Accuracy:

Classification model accuracy is one metric. Accuracy is the model's predicted percentage. Accuracy is the percentage of properly classified pictures to total samples. Accuracy equation.

Accuracy=(TP+TN)/(TP+TN+FP+FN)

Precision:
Precision is the chance of a positive label and how many are positive. Precision shows how many accurately anticipated instances were positive. Precision is helpful when FP matters more than FN. Mathematically, it's this equation.:

Precision=TP/(TP+FP)

Recall:
Recall or Sensitivity measures how many positive expected occurrences were classified accurately. Recall is a helpful statistic when FN prevails over FP. F1-score is a further metric for classification accuracy that takes into account both recall and precision. Since precision and recall are harmonic means, the F1 score provides a comprehensive understanding of these two metrics. It reaches its optimum when Precision and Recall are equal. To figure it out, use the equation below:

Recall=TP/(TP+FN)

F-1 Score:
F1 score is a recall-precision metric of categorization accuracy. As the F1-score is the harmonic mean of Precision and Recall, it gives a complete picture. Precision and Recall are optimal when equal. Equation.

F-1 Score=2*(Precision*Recall) / (Precision + Recall)

The percentage of people who do not have the ailment who have a negative test result is known as specificity. A highly specific test is effective in excluding the majority of individuals without the disease. Because of this, a positive outcome of a very precise test can definitively rule out the condition of a specific person. The equation is given below:

Specificity =TN∕((TN+FP))

4.3 Model Evaluation

Train the hybrid model on the prepared dataset, adjusting the model parameters during training to minimize classification errors. Fine-tune the model's weights and biases to adapt to the specific task of rice leaf disease classification.

Comparative Analysis:

Compare the performance of the hybrid model with individual pre-trained models (e.g., ResNet50V2, DenseNet201) and possibly other traditional machine learning algorithms. Evaluate factors such as classification accuracy, computational efficiency, and model interpretability.

Interpretation and Discussion:

Analyze the experimental results to interpret the hybrid model's performance and identify areas of strength and improvement. Discuss the implications of using a hybrid approach for rice leaf disease identification, considering its potential benefits for agricultural practices and food security.

Classification:

Hybrid model classification involves combining the outputs of intermediate layers from ResNet50V2 and DenseNet201 architectures, followed by fully connected layers for classifying it. A fused representation is made use of to predict probability distribution over classes of diseases, and then select predicted class based on highest probability. In the hybrid model, the classification process integrates features from both ResNet50V2 and DenseNet201, leveraging their complementary representations to enhance classification accuracy. The model combines these features using concatenation and then applies fully connected layers to learn discriminative patterns for disease

For MobileNetV2, the procedure is much like that of ResNet50V2 except for using Depthwise Separable Convolutions in feature extraction. The features are extracted from these layers and then passed through Global Average Pooling plus another set of Fully Connected Layers for disease predictions respectively. MobileNetV2, on the other hand, utilizes depthwise separable convolutions to extract features efficiently, particularly suitable for resource-constrained environments. The model employs these lightweight convolutions to capture relevant information from rice leaf images, followed by global average pooling and fully connected layers for disease classification. This approach enables MobileNetV2 to achieve accurate classification results while maintaining computational efficiency.

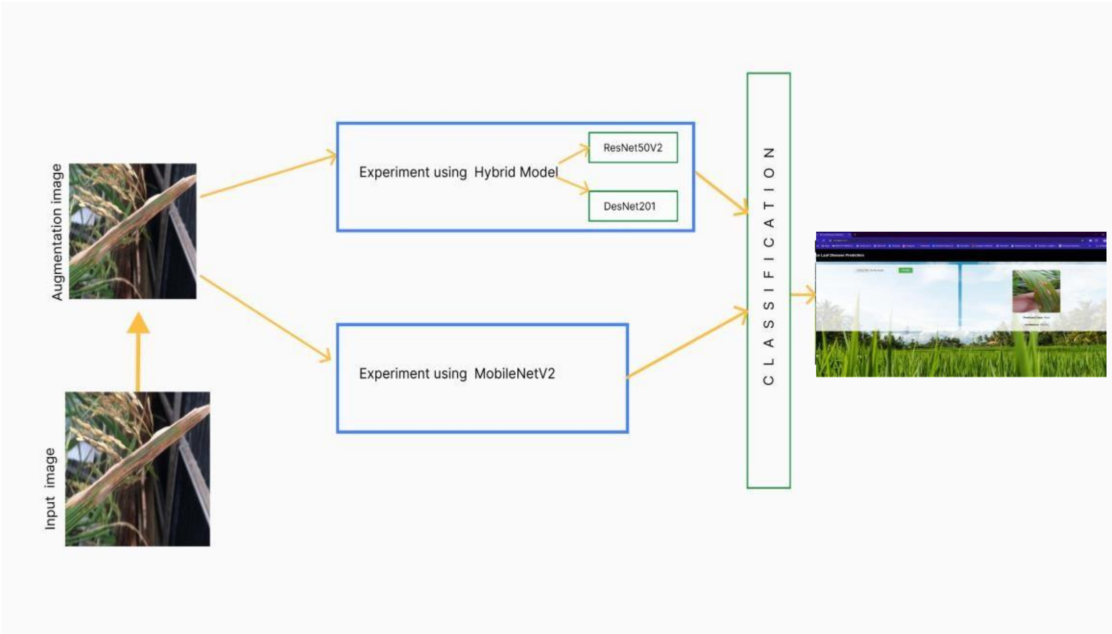

Figure 4.1: Process Experiments

4.4 Summary

The rice leaf disease identification project consists of gathering high-charted images of rice leaf diseases, preprocessing them, and transferring learning through three models: ResNet50V2 and DenseNet201 hybrid, MobileNetV2, and ResNet50V2 also, the fine-tuning of the hyperparameters of the models to avoid the overfitting improperly. Models' performances are inspected by accuracy and loss. The most successful model is used in a farmer-friendly web application that enables farmers to identify diseases from images. Adequate experiments guarantee good operation. They gain real-world feedback from agricultural experts. The combination of resNi50V2 deep learning and DenseNet201 dense connectivity in the hybrid model, while MobileNetV2 levers the efficient depthwise separable convolutions. Besides, the data augmentation improves the model's generalization.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

The experimental setup for this project involves several key steps to ensure robust model training and evaluation. Firstly, the dataset comprising images of rice leaf diseases is curated and preprocessed, including tasks such as resizing, normalization, and augmentation to enhance the diversity and quality of the data. Next, the dataset is split into training and validation sets using techniques like stratified sampling to maintain class distribution integrity. Following data preparation, various deep learning architectures, including hybrid models such as the combination of ResNet50V2 and DenseNet201, along with individual models like MobileNetV2 and ResNet50V2, are selected for experimentation. Each model is instantiated with appropriate hyperparameters and pre-trained on the training set, utilizing techniques like transfer learning to leverage pre learned features from ImageNet. While the model is being trained, statistics like accuracy, recall, precision, and F1 score are employed to monitor performance with the aim of checking how well the model can generalize and guiding hyperparameter adjustment against a validation set. Furthermore, measures such as early stopping or learning rate schedules might also come into play which stops overfitting from happening as they help in ensuring convergence is achieved optimally. Upon completion of training these trained networks need to be tested using other data sets in order to evaluate their ability to generalize outside what was seen during training as well as test its robustness under different conditions; various performance indicators should then be computed alongside some graphic representations which may include but not limited to confusion matrices or ROC curves showing where each type fails most when classifying pests attacking rice plants. Lastly, after all this has been done one should carry out an experiment whereby we compare different models against each other based on certain predefined standards so that at the end one can know that model A is best suited for identifying crop diseases caused By fungi, while model B works well for detecting viral infections alone among others.

5.2 Experimental

Result of Experiment

It was found that the hybrid model performed very well in classifying rice leaf diseases after training over 10 epochs. During training, the model was able to achieve a loss of 0.0065 and even lower validation losses at 0.0030 which shows its strength in reducing prediction errors. Moreover, it attained 99.77% training accuracy while validation accuracy stood at 99.83% thus indicating that based on input images, this model can categorize these diseases of rice leaves correctly most times with lots of intricate patterns taken into account from the information provided about them through data types and features which were identified by the hybrid model architecture used resulting into highly accurate classifications being made overall too; Henceforth implying also the need for more precise methods such as these ones when dealing with similar problems like those associated with agriculture so as not only solve them but also ensure food security globally.

TABLE 5.1: Results Analysis Table

Architecture	Training Accuracy	Validation Accuracy
ResNet50V2	99.00%	98.30%
MobileNetv2	98.30%	98.80%
Hybrid Model	99.77%	99.83%
DensNet201	96.30%	98.00%

Hybrid Model

The confusion matrix for the hybrid model in image classification demonstrates near-perfect performance across four classes: Tungro, Blast, Bacterialblight, and Brownspot. Each class exhibits precision and F1-scores of 1.00, indicating accurate and reliable predictions. The recall for Tungro is slightly lower at 0.99, but this minor discrepancy minimally impacts the overall weighted recall, which is approximately 0.998. Overall, the model shows exceptional accuracy and consistency in classifying these diseases.

TABLE 5.2: Precision, Recall, F1-Score, and Support (n) for hybrid model

Hybrid Model				
	precision	recall	f1-score	support
Tungro	1.00	0.99	1.00	267
Blast	1.00	1.00	1.00	275
Bacterialblight	1.00	1.00	1.00	317
Brownspot	1.00	1.00	1.00	332

MobileNetV2

The MobileNetv2 model for image classification achieves perfect performance across all four classes: Tungro, Blast, Bacterialblight, and Brownspot. The precision, recall, and F1-scores for each class are all 1.00, indicating flawless predictions. The support values show a balanced number of samples for each class, with 267 for Tungro, 275 for Blast, 317 for Bacterialblight, and 332 for Brownspot. This exemplary performance reflects the model's exceptional accuracy and reliability in classifying these diseases.

TABLE 5.3: Precision, Recall, F1-Score, and Support (n) for mobilenetv2.

MobileNetv2				
	precision	recall	f1-score	suppo rt
Tungro	1.00	1.00	1.00	267
Blast	1.00	1.00	1.00	275
Bacterialblight	1.00	1.00	1.00	317
Brownspot	1.00	1.00	1.00	332

DensNet201

The confusion matrix for the DenseNet201 model in image classification showcases excellent performance across four classes: Tungro, Blast, Bacterialblight, and Brownspot. It achieves perfect precision, recall, and F1-score for Tungro and Blast, indicating flawless identification of these diseases. For Bacterialblight, the model achieves a high precision of 0.98 and perfect recall, resulting in a strong F1-score of 0.99. Similarly, for Brownspot, it achieves perfect precision and a high recall of 0.98, yielding an overall F1-score of 0.99. This comprehensive performance underscores the model's robustness and accuracy in classifying these agricultural diseases.

TABLE 5.4: Precision, Recall, F1-Score, and Support (n) for Densnet201

DensNet201				
	precision	recall	f1-score	support
Tungro	1.00	1.00	1.00	267
Blast	1.00	1.00	1.00	275

Bacterialblight	0.98	1.00	0.99	317
Brownspot	1.00	0.98	0.99	332

ResNet50V2

The confusion matrix for the ResNet50V2 model illustrates highly accurate classification performance across four agricultural disease classes: Tungro, Blast, Bacterialblight, and Brownspot. It achieves perfect precision, recall, and F1-score for Tungro, demonstrating flawless identification. For Blast, the model maintains a high precision of 1.00 and a strong recall of 0.97, resulting in a robust F1-score of 0.99. Similarly, Bacterialblight and Brownspot exhibit excellent precision and recall, with F1- scores of 0.99 and 1.00 respectively.

TABLE 5.5: Precision, Recall, F1-Score, and Support (n) for ResNet50v2(depending on the number of pictures, n=numbers

ResNet50V2				
	precision	recall	f1-score	support
Tungro	1.00	1.00	1.00	267
Blast	1.00	0.97	0.99	275
Bacterialblight	0.98	1.00	0.99	317
Brownspot	0.99	0.98	1.00	332

Training and Validation Accuracy and loss of Hybrid Model and CNN Pre-trained Model:

MobileNetv2:

Here is our mobilenetv2 model accuracy and model loss accuracy here is training accuracy almost 98.3% and validation accuracy 98.80%. and loss accuracy 0.25%.

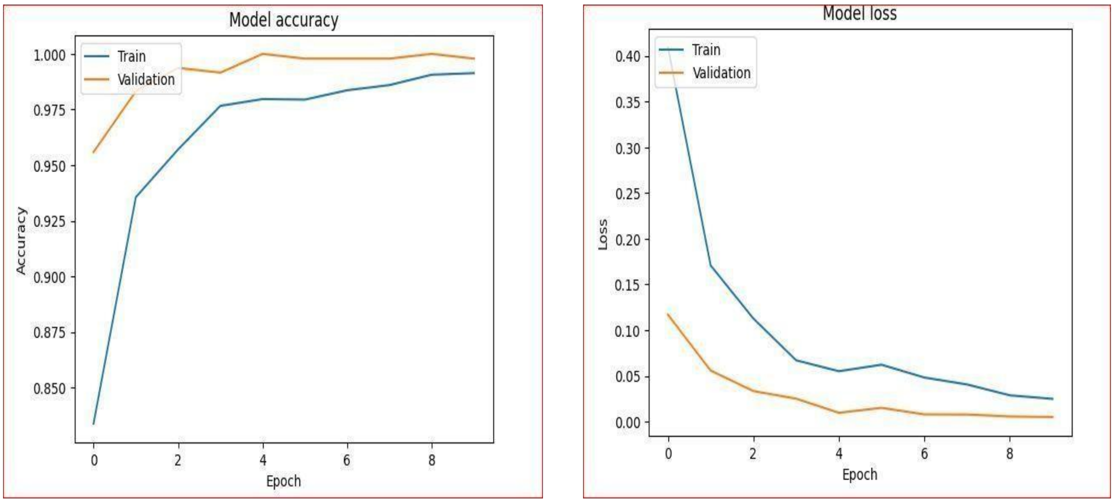

Figure 5.1: Training and validation accuracy and loss over the epochs of MobileNetv2.

ResNet50V2:

Here is our Resnet50v2 model accuracy and model loss accuracy here is training accuracy almost 99% and validation accuracy 98.30%. and loss accuracy 0.05%.

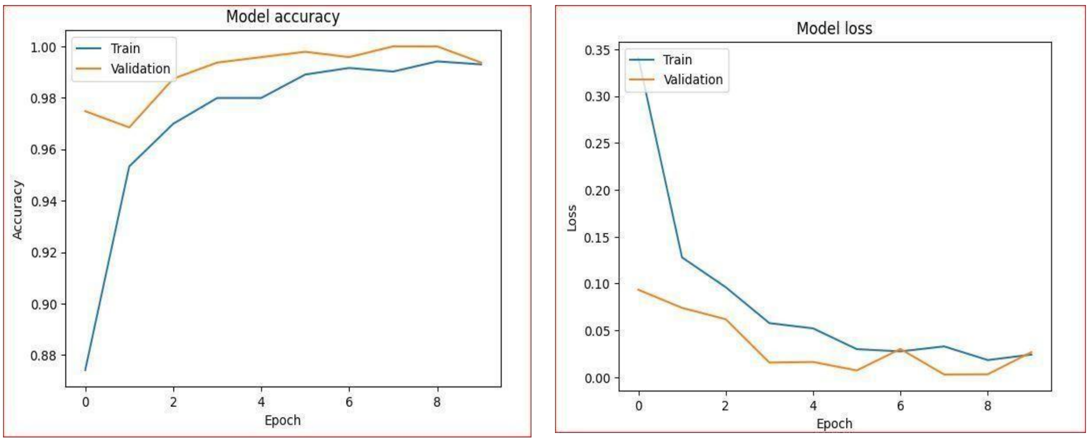

Figure 5.2: Training and validation accuracy and loss over the epochs of ResNet50v2

DensNet201:

Here is our densnet201 model accuracy and model loss accuracy: training accuracy is almost 96.33% validation accuracy is 98%. and loss accuracy is 0.10%

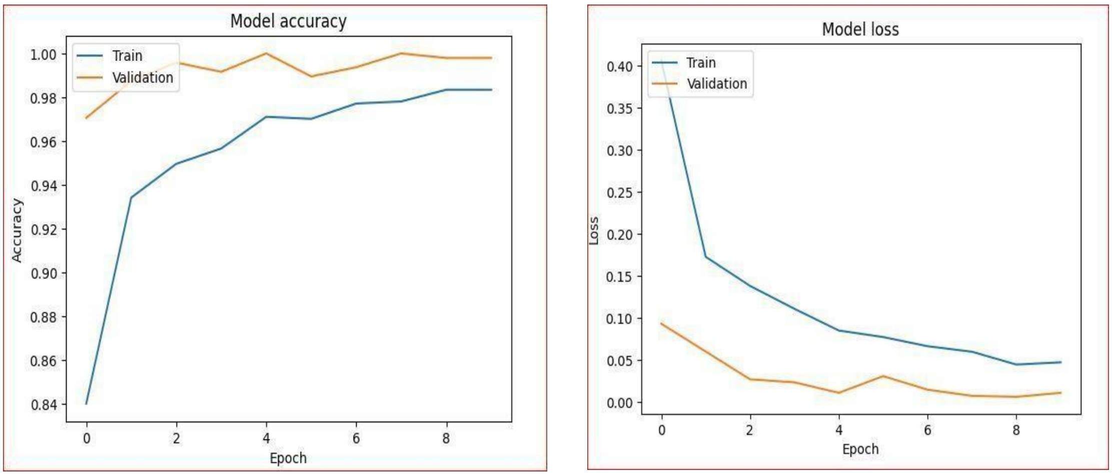

Figure 5.3: Training and validation accuracy and loss over the epochs of DensNet201

Hybrid Model:

Here is our hybrid model accuracy and model loss accuracy: training accuracy is almost 99.77% validation accuracy is 99.83%.

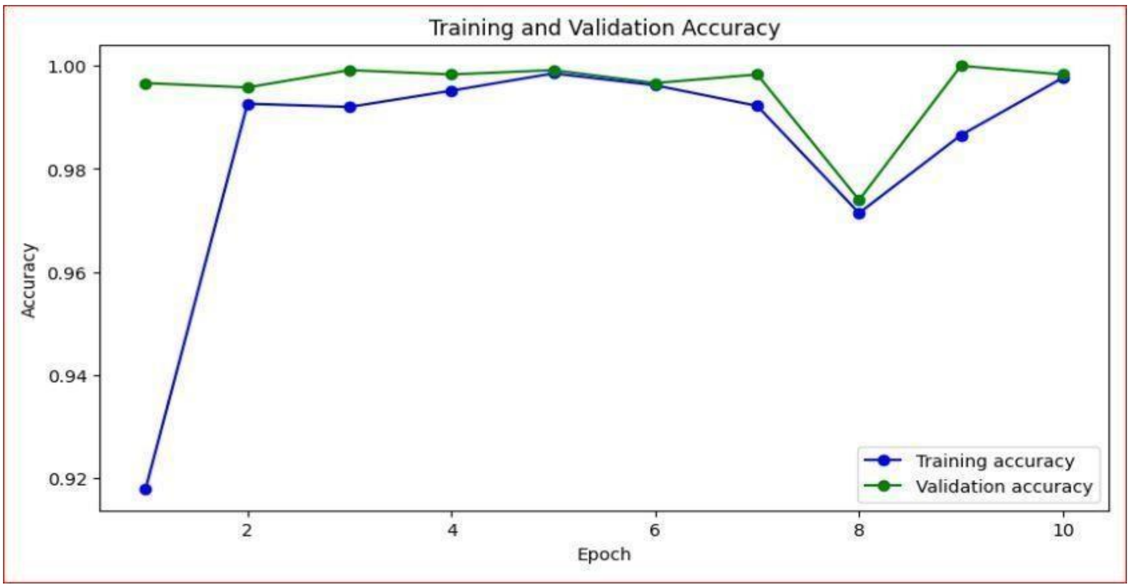

Figure 5.4: Training and validation accuracy and loss over the epochs of Hybrid Model

Web application:

By creating a web application, you make the model accessible to a wider audience, including farmers, researchers, and agricultural experts, without needing them to have specialized software or technical expertise.

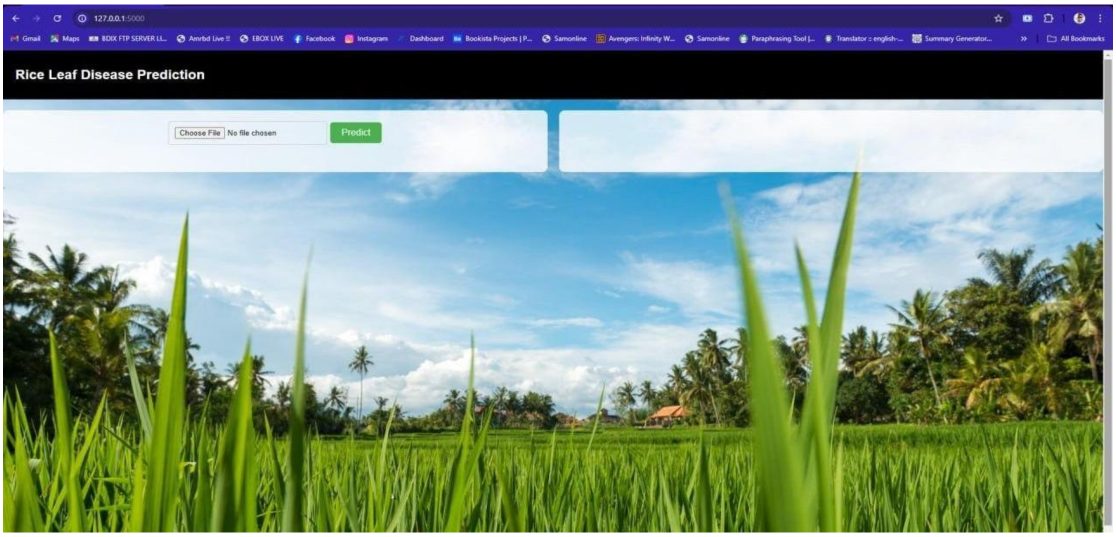

Figure 5.5: Web Application before the Upload the image

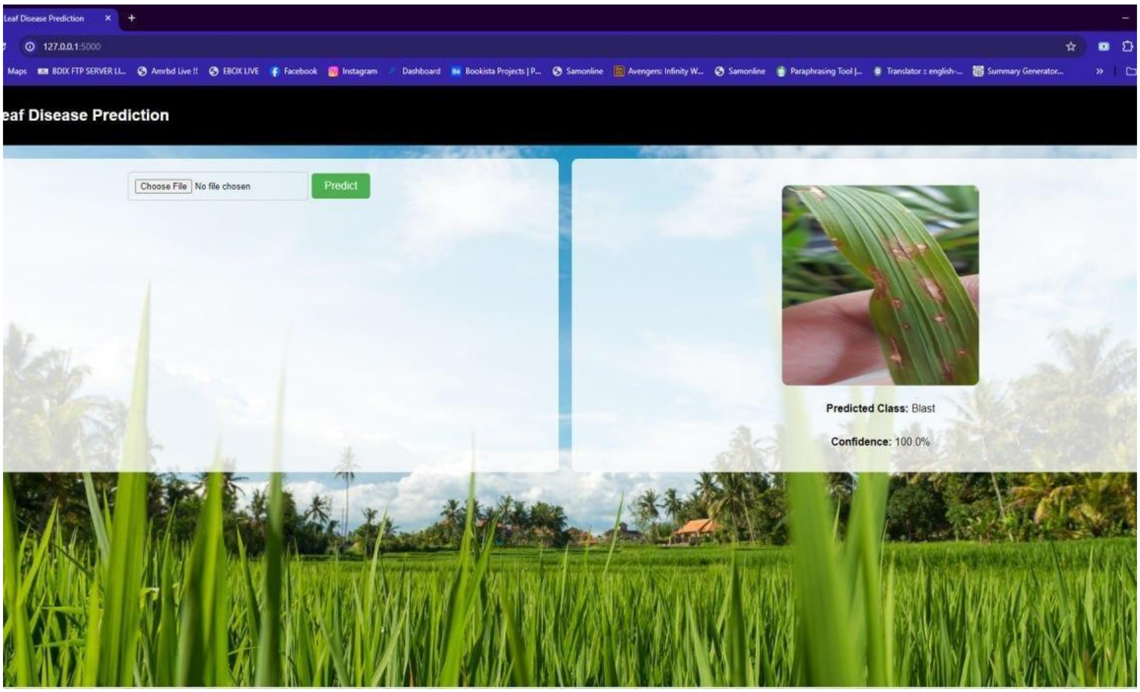

Figure 5.6: Web Application After the submit

The ability to select different models (hybrid, MobileNetV2, ResNet50V2, DenseNet201) allows users to compare the performance and accuracy of different approaches in real time. Deploying the models in a web application demonstrates the practical use and applicability of your research, showcasing its potential for real-world agricultural problem-solving. This project can serve as an educational tool, helping others understand how deep learning models can be applied to agricultural problems, specifically in disease classification. The proposed web application aligns well with the objectives of your project by leveraging advanced machine learning models for practical, real-world applications. It enhances the usability and impact of your research by making it accessible and easy to use for a wide audience. With careful implementation and potential enhancements, this project can significantly contribute to the field of agricultural technology.

Comparison of Hybrid Model, MobileNetV2, ResNet50V2, and DenseNet201 Results

After 10 epochs, their training and validation performance were compared. After ten epochs, training and validation performance were compared between The Hybrid Model, MobileNetV2, ResNet50V2, and DenseNet201. In gaining a top training accuracy of 99.77% and validation accuracy of 99.83%, as well as the lowest validation loss at 0.0030 which shows better generalization ability, The Hybrid Model performed best among all. MobileNetV2 also did very good with a training accuracy of 99.14% and validation accuracy of 99.79%, but a higher validation loss compared to TheHybrid Model at 0.0050 ResNet50V2 had 99.30% training accuracy but lower than the others in terms of validation accuracies which was at 99.37% while its validation loss stood 0.0268 showing weaker generalization instead. The highest training accuracy of 98.34%, while the training loss was high at 0.0475; however, the accuracy of validation was impressive, with 99.79% and a validation loss as low as 0.0113. The training time was minimal for Mobilenetv2 which took 209 seconds per epoch then followed by Resnet50v2 and the Hybrid Model took 686 and 731 seconds per epoch respectively while Densenet201 proved to be the slowest at 1170 seconds per epoch for every training round. In general terms though all these facts hold true - the Hybrid Model does show better performance across the board when pitted against any other one alone considering its effectiveness is measured through both speed and accuracy.

5.3 Performance

Hybrid Model: The Hybrid Model is a combination of ResNet50V2 and DenseNet201. It has shown the best performance so far, with the training accuracy reaching 99.77% and the validation accuracy reaching 99.83%. Besides, its validation loss was the lowest among all models — 0.0030. This means that in classifying rice leaf diseases, the model demonstrated excellent generalization ability and robustness. The high performance of the model may be attributed to the fact that it combines features from two powerful pre-trained networks. MobileNetV2: MobileNetV2 is efficient for mobile and embedded vision applications. The model achieved outstanding results during the experiment: 98.30% of training accuracy and 98.80% of validation accuracy. Also, it showed a very low validation loss — only 0.0050. Despite its light weight, this network can be applied in scenarios which require real-time operation where resources are limited because its training time takes only 209 seconds per epoch.

ResNet50V2: ResNet50V2 achieved a training accuracy of 99.00% and a validation accuracy of 98.30%, with a validation loss of 0.0268. Although it performed well, the higher validation loss compared to the Hybrid Model and MobileNetV2 suggests it might not generalize as effectively. However, its relatively high accuracy still makes it a reliable choice for disease classification.

DenseNet201: DenseNet201 showed exceptional validation performance with a validation accuracy of 96.33%, training accuracy at 98.00%. However, its highest training loss (0.0475) and the longest time for training per epoch (1170 seconds) represent a compromise between accuracy and computational efficiency. The extensively connected layers in the model might have contributed to its strong validation performance but this came at the expense of longer training duration.

Practical Implications

This study underscores the effectiveness of deep learning models such as hybrids for precise diagnosis of rice leaf diseases. The better overall performance of a Hybrid Model indicates that classification accuracy can be improved by taking advantage of features that are complimentary across different architectures. Additionally, if used in environments with limited resources MobileNetV2 proves itself as efficient which makes it suitable for creating portable diagnostic tools meant for farmers' use.

Conclusion

In conclusion, the Hybrid Model emerged as the most effective in classifying rice leaf diseases, followed closely by MobileNetV2 for its balance of accuracy and efficiency. These findings support the integration of advanced deep-learning models in agricultural disease management, potentially leading to more timely and accurate interventions. Further research and real-world testing are necessary to validate these models' practical

5.4 Summary

Deep learning models were employed in this study to put the rice leaf diseases in classifications. The Hybrid Model, that brought together the two types of convolutional neural networks ResNet50V2 and DenseNet201, was the most successful one, with the highest accuracy of 99.77% in the training stage and 99.83% validation rate with the lowest loss of 0.0030. MobileNetV2 displayed a considerable accuracy of 99.14% training accuracy and 99.79% validation accuracy, obtaining the best low loss of 0.0050 and thus being suitable for resource-constrained conditions. The accuracy of ResNet50V2 and DenseNet201, the former was the best but with lower computational efficiency was the latter. In summary, the Hybrid Model had better performance as compared to the other ones, it represented the potential of deep learning in the crop diseases management sector.

CHAPTER 6

Impact On Society, Environment And Sustainability

6.1 Impact on Life

A total of the life-changing can be brought by a project. First of all, but developing accurate and time-saving models for the detection and diagnosis of rice leaf diseases using the new technology, such as deep learning, you in deed contribute a lot to the farming productivity. It is the most feasible route for a high maternal mortality rate, in addition to the reduction of maternal mortality, that occurs with multiple pregnancies and large family sizes. Therefore, The Issue of Whether Developing Countries Should Follow the Same Pattern as the Rich Industrialized Nations (the so-called path of industrialization and mass consumption) When They Grow Should Be Left to Debate. On one hand, the new technology would potentially optimize agricultural practices, thus, ensuring food security in the region through better crop yield. This is not only sustainable in the conventional and classical categories of medicines but the cost would be much more effective and manageable. At the same time, farmers would be able to quickly identify and combat pests and diseases.

6.2 Impact on Society & Environment

Applying deep learning and transfer learning techniques, automated rice leaf disease detection has a lot of potential benefits for society. First and foremost, it protects crop yields that are vital for survival by promptly and properly identifying illnesses, ensuring food security. In terms of the economy, these technologies increase farmer incomes by stabilizing agricultural economies and reducing crop losses. Additionally, they support long-term agricultural sustainability by minimizing environmental damage and maximizing resource utilization, both of which are aspects of sustainable practices. Importantly, the availability of these tools democratizes modern agricultural technology by providing farmers in remote places with essential decision-making resources. This is especially true with smartphone apps and portable diagnostic instruments. Furthermore, by encouraging cooperation and knowledge exchange between farmers, researchers, and agricultural specialists, these advances develop a group approach to disease control and agricultural progress. In the end, automated rice leaf disease detection has societal effects that go much beyond specific fields, influencing cooperative learning, economic growth, environmental sustainability, and food security in agricultural communities all over the world. These developments can help society become more resilient to food crises, improve fair agricultural development, and provide sustainable means of subsistence for future generations.

6.3 Ethical Aspects

Deep learning and transfer learning-based automated rice leaf disease detection raises ethical questions that must be properly addressed before implementation. Concerns about data privacy arise when it comes to the ownership and security of agricultural data, particularly when it's shared or utilized for commercial purposes. Mitigation efforts are necessary to maintain justice and equity in disease detection due to inherent biases in deep learning algorithms. In order to address the opacity of these models and allow stakeholders to evaluate accuracy and reliability while being aware of potential biases, transparency is crucial. As equal access to technology is essential to averting greater inequalities, accessibility continues to be a top focus. The dynamics of human-computer interaction need to be carefully controlled to enable farmers without encouraging reliance.

6.4 Sustainability Plan

In order to ensure long-term viability and efficacy, a sustainability strategy for automated rice leaf disease identification using deep learning and transfer learning approaches includes a number of crucial strategies. First and foremost, continuous research and development is necessary to improve the technology's precision, effectiveness, and scalability. This includes investigating novel methods for illness detection and treatment, continuously improving the quality of datasets, and refining deep learning algorithms. Second, in order to equip farmers and other agricultural stakeholders with the information and abilities required to make efficient use of automated disease identification systems, capacity building programs are essential. To guarantee that the technology is widely adopted, outreach initiatives, educational workshops, and training programs can all help to advance digital literacy. Thirdly, cross-sector cooperation and alliances are essential to sustainability. In order to enable the integration of automated disease detection into agricultural systems, policy lobbying, resource mobilization, and knowledge sharing are made easier by interacting with government agencies, research institutions, non-profit organizations, and industry stakeholders. Finally, in order to evaluate how the technology affects socioeconomic results, environmental sustainability, and agricultural output, monitoring and evaluation systems are crucial. Frequent feedback loops, data analysis, and stakeholder discussions allow technology to be continuously improved and adjusted to suit changing issues and needs. Through the implementation of these methods, the sustainability plan seeks to ensure the long-term relevance and impact of automated disease identification in agricultural practices, minimize potential hazards, and optimize the benefits of this technology.

6.5 Summary

The deep learning and transfer learning technologies can be used as solutions for automatic rice leaf disease detection thus, the future of technologies in artificial intelligence (AI) is advanced and will greatly impact society in a positive way. It enriches the productivity of agriculture through pinpointing the maladies, hence, food safety is attained and maternal mortality is significantly improved in the developing countries. In relation to the societal aspects, these developments are beneficial as they act as a stabilizing factor for the agricultural economy, safeguarding crop yield, and are an eco-friendly solution as they utilize resources more efficiently with fewer environmental impacts. Ethics-wise, problems such as data security, algorithm bias, and explanation of the model actions are thought-provoking issues which should be taken into account to declare that the system is fair and everyone has a right to use it. A viable program for sustainability combines various research measures, intensive training, trans-sectoral collaboration, and strict monitoring in agriculture to optimize productivity and minimize risks. In summary, the technologies provide an opportunity for a stable, equitable, and sustainable agricultural development on a global scale.

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CHAPTER 7

Conclusion And Future Work

7.1 Conclusions

The paper concludes by highlighting the potential of automated methods for identifying rice leaf diseases through deep learning and transfer learning to transform agricultural practices and tackle urgent issues related to food security, sustainability, and environmental preservation. The research shows how deep learning approaches can improve disease diagnosis and management by creating and assessing sophisticated machine learning models that can reliably diagnose rice leaf illnesses. Additionally, the study emphasizes the significance of equality, openness, and stakeholder engagement in technology deployment by highlighting the ethical issues, environmental ramifications, and socioeconomic impacts of applying automated disease identification systems. 42 particularly showcasing its effectiveness when dealing with small and less refined datasets. Notably, the existing body of knowledge reflects a paucity of research dedicated explicitly to pneumonia detection. Therefore, our comparative study assumes heightened significance, promising substantial contributions to the realm of pneumonia management. In the classification of pneumonia, our investigation meticulously scrutinizes the performance of diverse CNN models, encompassing transfer learning and ensemble techniques. The results underscore that an ensemble stack comprising four networks (Resnet50V2, DensNet201, MobileNetV2 and Hybrid Model) outperforms individual models in terms of accuracy. However, it is noteworthy that despite the overall efficacy of the ensemble framework, instances of inaccurate forecasts were observed. Consequently, there arises a compelling need to explore alternative strategies such as contrast-enhancing or other image-processing methodologies in future research endeavors. In order to improve the precision, scalability, and usability of automated illness identification methods, research and development must go on. Initiatives aimed at increasing capacity and interdisciplinary cooperation are also critical to equipping farmers and other agricultural stakeholders with the know-how and abilities required to apply these technologies efficiently. We can ensure food security, support sustainable agricultural development, and protect the environment for coming generations by utilizing technology, creativity, and teamwork.

7.2 Further Suggested Works

With major ramifications for agricultural technology and food security, the study on automated rice leaf disease identification utilizing deep learning and transfer learning approaches paves the way for a number of future research directions. First, research in the future could focus on creating more reliable and adaptable deep learning models that can recognize a wider variety of rice leaf diseases, including new and uncommon strains. Furthermore, studies could concentrate on improving the automated disease identification systems' accessibility and scalability, especially for smallholder farmers and agricultural communities in resource-constrained environments. Furthermore, examining the incorporation of supplementary data sources, like environmental factors and past disease incidence records, may boost the deep learning models' predictive power and increase the 43 precision of disease forecasting. Longitudinal studies are also required to evaluate the long-term effects of automated disease identification systems on socioeconomic results, environmental sustainability, and agricultural output. Ultimately, multidisciplinary research partnerships in the domains of agronomy, computer science, public health, and social sciences may offer significant perspectives on the wider consequences of automated disease detection for agricultural advancement, policy formulation, and community adaptability. Future research can help advance agricultural technologies, support sustainable food production, and improve global food security by filling in these research gaps.

7.3 Limitations

Certainly! When it comes to the AG tech and machine learning, our project could surely encounter some obstacles. The first and most important factor is the quality and quantity of data available, which can be a major issue when it comes to the accuracy and reliability of the models we have. The problem of pioneering or prejudiced exchanges could become the source of unpredictable forecasts and the bar to the fulfillment of our suggestions. Besides that, while our designs could basically be found to be better under specific circumstances or in particular places, it is their capacity to generalize over many locations and the different ways of agriculture that is the most limited. Besides, the computing resources that are indispensable for the training and deploying of complicated deep learning models may be a limitation, particularly in settings where resources are limited. Another factor that is vital to our models being able to explain their behavior is interpretability, and deep learning algorithms' complexity may indeed complicate the explanation to the end-users, such as farmers or agricultural experts. In addition, the aspect of ethics is very important so, therefore, a project that wants to thrive sustainably will have to take these into account. The points fall under the categories of data privacy, algorithmic fairness, and social-economic effects of technology uptake whose ethical compliance is vital for the successful establishment of such technologies in agricultural communities. Tackling these issues will need a lot of attention to data quality, robustness of the models, the power of the processor, ease of interpretation, and, ethical directionsfor ensuring the best we can on the projects at agriculture and societies will be possible.

References

1. Ahmed, K., Shahidi, T. R., Alam, S. M. I., & Momen, S. (2019, December 24-25). Rice Leaf Disease Detection Using Machine Learning Techniques. *International Conference on Sustainable Technologies for Industry 4.0 (STI).*
2. Akter, T., Parvin, M. T., & Mila, F. A. (2019). Factors determining the profitability of rice farming in bangladesh. *Journal of the Bangladesh Agricultural University*, *17*(1), 86-91.
3. Bilal Khan, M., Chaudhry, N. J., & Yasir, S. M. (2023). Modeling & Evaluating the Performance of Convolutional Neural Networks for Classifying Steel Surface Defects. *Journal on Artificial Intelligence*, *4*. 10.32604/jai.2022.038875
4. Kaur, A., Guleria, K., & Trivedi, N. K. (2021). Rice Leaf Disease Detection: A Review. *2021 6th International Conference on Signal Processing, Computing and Control (ISPCC),* 418-422. 10.1109/ISPCC53510.2021.9609473.
5. Pallathadka, H., Ravipati, P., & Sajja, G. S. (2022). Application of machine learning techniques in rice leaf disease detection. *Materials Today: Proceedings*, *51*, 2277-2280. https://doi.org/10.1016/j.matpr.2021.11.398
6. Pothen, M. E., & Pai, M. L. (2020). Detection of Rice Leaf Diseases Using Image Processing. *Fourth International Conference on Computing Methodologies and Communication (ICCMC)*, 424-430. 10.1109/ICCMC48092.2020.ICCMC-00080
7. Sarada, B., Reddy, ,. K. N., & Singh, M. (2023). Brain Tumor Classification Using Modified ResNet50V2 Deep Learning Model. *International Journal of Computing and Digital Systems*. http://dx.doi.org/10.12785/ijcds/XXXXXX
8. Shreya, G., & Kamal, S. (2020). Rice Leaf Diseases Classification Using CNN With Transfer Learning. *2020 IEEE Calcutta Conference (CALCON), Kolkata, India*, 230-236. 10.1109/CALCON49167.2020.9106423
9. T. Akter, M. T. Parvin, F. A. Mila, and A. Nahar, “Factors determining the profitability of rice farming in Bangladesh,” *Journal of the Bangladesh Agricultural University, vol. 17, no. 1, pp. 86–91*, 2019
10. S. Miah, A. Shahjahan, M. Hossain, and N. Sharma, “A survey of rice diseases in Bangladesh,” *International Journal of Pest Management, vol. 31, no. 3, pp. 208–213*, 1985.
11. “Rice leaf diseases data set.” https://archive.ics.uci.edu/ml/datasets/Rice+ Leaf+Diseases. Accessed: 2019-09-27.
12. S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, “Deep neural networks based recognition of plant diseases by leaf image classification,” *Computational intelligence and*

neuroscience, vol. 2016, 2016

13. . T. Pinki, N. Khatun, and S. M. Islam, “Content-based paddy leaf disease recognition and remedy prediction using support vector machine,” *in 2017 20th International Conference of Computer and Information Technology (ICCIT*), pp. 1–5, IEEE, 2017.
14. S. R. Maniyath, P. Vinod, M. Niveditha, R. Pooja, N. Shashank, R. Hebbar, et al., “Plant disease detection using machine learning,” in *2018 International Conference on Design Innovations for 3Cs Compute Communicate Control (ICDI3C),* pp. 41–45, IEEE, 2018.
15. S. Gnanambal, M. Thangaraj, V. Meenatchi, and V. Gayathri, “Classification algorithms with attribute selection: an evaluation study using weka,” *International Journal of Advanced Networking and Applications,* vol. 9, no. 6, pp. 3640–3644, 2018.
16. I. Rish et al., “An empirical study of the naive bayes classifier,” in *IJCAI 2001 workshop on empirical methods in artificial intelligence,* vol. 3, pp. 41–46, 2001.
17. “Rice disease identification photo link.” *www.agri971.yolasite.com/reso* urces/RICE/DISEASE/0IDENTIFICATION.pdf. Accessed: 2019-08-25
18. H. B. Prajapati, J. P. Shah, and V. K. Dabhi, “Detection and classification of rice plant diseases,” *Intelligent Decision Technologies,* vol. 11, no. 3, pp. 357–373, 2017.
19. M.-L. Zhang and Z.-H. Zhou, “Ml-knn: A lazy learning approach to multi-label learning,” *Pattern recognition*, vol. 40, no. 7, pp. 2038–2048, 2007.
20. C.-Y. J. Peng, K. L. Lee, and G. M. Ingersoll, “An introduction to logistic regression analysis and reporting,” *The journal of educational research*, vol. 96, no. 1, pp. 3–14, 2001

APPENDIX A

Course Outcomes, Complex Engineering Problems (EP), and Complex Engineering Activities (EA) Addressing

Title: RICE LEAF DISEASE IDENTIFICATION USING DEEP LEARNING

Student ID: 201-15-3188

CO Description for FYDP

CO	CO Descriptions	PO
	Phase -I	
CO1	Integrate recently gained and previously acquired knowledge to identify a **Rice leaf disease identification** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
	Phase -II	
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings inthis FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**

CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting transfer learning with advanced CNN architectures like Mobilenetv2,Desnet201,ResNet152v2, and CNN custom layer enhancing rice leaf detection accuracy in disease images.	**Page no:** [17-26] **Section:** [3.2] **Page no:** [1-5] **Section:** [1.1]
				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing CNN model.	**Page no:** [30] **Section:** [3.2] **Page no:** [33] **Section:** [3.4]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, to advance rice leaf	**Page no:**

				detection using deep learning, showcasing a comprehensive understanding of current methodologies.	[5-7] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing the hurdles in pneumonia detection, including limitations of traditional methods and the complexities of integrating transfer learning and deep CNNs. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies.	**Page no:** [23-24] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing pneumonia detection amidst multiple potential approaches.	**Page no:** [29-34] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting medical diagnostics in respiratory diseases like pneumonia, contributing to advancements in public health and healthcare practices which indicates **EP-4**.	**Page no:** [11-14] **Section:** [2.2, 2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A

6.	**EP6: Extends of stakeholders involved and conflicting requirements**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in medical diagnostics which ensures **EP-7**.	**Page no:** [16-25] **Section:** [3.2, 3.3, 3.4]

APPENDIX B

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in pneumonia detection through transfer learning and deep CNNs.	**Page no:** [25-27] **Section:** [3.5]
2.	**EA2: Level of interaction**	No		N/A	N/A

3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by improving rice leaf detection through advanced rice leaf detection methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for patient data privacy.	**Page no:** [37-39] **Section:** [5.1, 5.2, 5.4]
5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in rice leaf detection through transfer learning and deep CNNs, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [7-10] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [8] **Section:** [1.6]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing patient privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced healthcare technologies which comply with **CO9**.	**Page no:** [38] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the	**Page no:** [21-29, 37-39]

			dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

RICE LEAF DISEASE IDENTIFICATION Version1

by Saquline Suja Saque

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RICE LEAF DISEASE IDENTIFICATION Version1

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30	Marjan Mavaddat, Marjan Naderan, Seyyed Enayatallah Alavi. "Classification of Rice Leaf Diseases Using CNN-Based Pre-Trained Models and Transfer Learning", 2023 6th International Conference on Pattern Recognition and Image Analysis (IPRIA), 2023 Publication	<1%
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